Middle-East Journal of Scientific Research 25 (1): 40-48, 2017
ISSN 1990-9233

DOI: 10.5829/idosi.mejsr.2017.40.48

Improved Lossless Image Compression Model Using Coefficient Based Discrete Wavelet Transform

[1]T. Velumani and [2]S. Sukumaran

[1]Department of Computer Science, Kongu Arts and Science College, Erode, India
[2]Department of Computer Science, Erode Arts and Science College, Erode, India

Abstract: Compression is used for storage related applications that offers compression of audio/video, executable program, text, source code and so on. While compressing images into smallest space as possible, the constraint lies in the multispectral form of data with continuous images. In such a scenario, efficient lossless image compression is required such that the compression ratio can be improved and reduces the computational complexity. In this paper, we proposed a model called, Coefficient-based Discrete Wavelet Transform (CDWT) for lossless image compression which improves the compression ratio and reduces the computational complexity involved during transformation. The Coefficient-based Discrete Wavelet Transform initially partitions the image into coefficients to decide upon which coefficient value to be considered for encoding. Next, Probability-based Transformation for lossless image compression for continuous images follows Probability-based encoding to reduce the computational complexity involved during transformation. Extensive experiments carried out on the Waterloo color images have revealed the outstanding performance of the proposed CDWT model when benchmarked with various well established state-of-the-art schemes. The results obtained by CDWT witness a significant increase in compression ratio by reducing the total error while compressing with minimized computational complexity when compared with the results produced by the other state-of-the art methods considered.

Key words: Lossless image compression · Multispectral · Discrete Wavelet Transform · Probability-based encoding

INTRODUCTION

Visual surveillance is a task that often involves collecting a large amount of data in search of information contained in relatively small segments of images. Image compression methods play an important role in many applications with limited resources for viewing, storage and processing. Traditional image compression algorithms reduce the spatial cost of images by reducing the amount of data and allow users to act on the compression ratio of the image.

Binary Space Partition and Geometric Wavelets were applied in [1] for designing an improved image compression algorithm. The image compression algorithm designed resulted in the efficient compression ratio. Another innovative lossless compression method was introduced in [2] using Huffman code with the objective of enhancing the compression ratio. However, with the exponential growth in image size, compression ratio also deteriorated. To address this issue, visual masking model [3] was introduced for lossless encoding. Another binary compressed imaging [4] was investigated under total-variation regularization with the objective of providing reconstruction.

Most bio images significantly require compression either at the stage of transmitting or storing the images because of constrained bandwidths and limited storage capacity. In [5], with the objective of yielding high quality compressed image and compression ratio, Haar Wavelet Transform and Discrete Cosine Transform were designed to yield high compression ratio. Another model in [6] provided an insight into higher compression rate using psychovisual threshold on the large discrete cosine transform (DCT) image block. A survey on image compression algorithms was provided in [7]. A novel image compression for DNA sequences was presented in [8] aiming at achieving higher compression ratio.

Corresponding Author: T. Velumani, Department of Computer Science, Kongu Arts and Science College, Erode, India.

In this proposed work the Coefficient-based Discrete Wavelet Transform are applied to the images based on the threshold value with mean square. With the transformed images obtained as output, the Probability-based Transformation for lossless image compression for continuous images is applied aiming at reducing the computational complexity involved during transformation. The experimental results produced are used to find out the best performance among the existing and proposed lossless image compression models.

Related Works: In the context of medical image compression, the amount of data to be acquired can be substantially reduced as compared to conventional strategies. In [9], predictive coding network was experimented to natural and medical images aiming at improving the compression ratio. Another method based on VLSI was introduced in [10] aiming at not only improving the compression ratio but also enhancing the processing rate and processing time substantially. In [11], novel method based on Huffman coding was introduced for lossless image compression and decompression with the objective of providing better compression.

With the increase in the development of medical imaging and telemedicine, the application of image compression on medical images has risen to greater extent. In [12], Region of Interest based coding techniques was introduced to provide efficient compression ratio. However, the ratio of noise introduced varied with the increase in size of images. To address this issue, a Discrete Cosine Transform model [13] was introduced aiming at not only reducing the noise but also to provide good compression ratio. Simple arithmetic addition models [14] provided an insight into lossless image compression. A survey on image compression for optical space imaging system was introduced in [15] to achieve improved coding performance.

Based on the aforementioned methods and techniques in this paper, Transformation and Coefficient-based Discrete Wavelet Transform (CDWT) for lossless image compression is introduced that not only improves the compression ratio but also reduces the computational complexity involved during transformation of images.

Lossless Image Compression Based on Transformatuon Models: The transformation models for lossless image compression and its variants are widely used when it comes to storing or transmitting images. The transformation model based on Lapped Transform and Tucker Decomposition (LT-TD) [16] performs the hyperspectral image compression in a simple way. This works for most of the practical cases, with a wide variety of applications, significant data storage capacity necessary for imaging system, as the hyperspectral imaging system are larger in size.

The transformation model based on Open Computing Language (OpenCL) [17] and Discrete Cosine Transform merging the DCT and quantization showed a memory map mechanism reducing the CPU overhead and improving the compression performance. In Lossless Compression (LC) [18] method for Discrete Color Images, has the main idea of constructing fixed-to-variable codebook is that instead of using row-column values in images, it involves mathematical computations that removes redundancy in '8 * 8' *blocks* using row-column reduction coding. The Color Space Transformations (CST) [19] performs the color space transformations for lossless image compression in a simple way.

Image Compression Using Lapped Transform and Tucker Decomposition: A lossy compression system based on Lapped Transform and Tucker Decomposition (LT-TD) [16] was developed to improve compression performance. Firstly, LT was used to transform the hyperspectral image in the 2D spatial domain. The amount of the data was observed to be very large especially when the hyperspectral image is with spatially high-definition.

Therefore each spectral band of hyperspectral image was transformed into different frequency-bands and then they were processed as separate tensors. Then, different subbands were taken as tensors and were processed by TD or KLT. Finally, the Tucker tensors and other transformed coefficients were allocated to different bit rates and were encoded by the bit-plane coding algorithm resulting in the improvement of compression performance. The algorithm is given below (Figure 1).

The algorithm initially performs LT on each band 'H, V, Z'' with the given hyperspectral image as input. With LT having the basis function longer than the block size, the lengths of the pre-filter and DCT were assigned as '$2N$ and M' respectively. Once the two dimensional transform was accomplished, the coefficient in upper left corner were referred to as DC coefficient and the others as AC coefficient.

Input: Hyperspectral image 'I', Spatial resolution 'H, V, Z'

Step 1: For each Hyperspectral image 'I' and Spatial resolution 'H, V, Z'
// perform lapped transform on each band
Step 2: Set the basis function lengths of the pre-filter and DCT as '$2N$ *and* M' respectively
Step 3: Perform 2 dimensional transforms to obtain '$M * M$' blocky coefficients
Step 4: Assign upper left corner as DC coefficient
Step 5: Assign others as AC coefficient
Step 6: Arrange AC coefficient
Step 7: Arrange DC coefficient
Step 8: End for
//tensor tucker decomposition
Step 9: View transformed coefficients in 3d structure as third-order tensors
Step 10: For each tensors with sizes of '$\frac{H}{8} * \frac{V}{8} * Z$', '$\frac{H}{4} * \frac{V}{4} * Z$', '$\frac{H}{2} * \frac{V}{2} * Z$'
Step 11: Perform PCA on tensors
Step 12: End for

Fig. 1: Lapped Transform and Tucker Decomposition algorithm

Then the DC coefficients and AC coefficients were arranged where the transformed coefficients were viewed as '$\frac{H}{8} * \frac{V}{8} * Z$', '$\frac{H}{4} * \frac{V}{4} * Z$', '$\frac{H}{2} * \frac{V}{2} * Z$'. Finally, a one dimensional PCA was performed by decomposing into core tensor to reduce the computational complexity and improving the compression performance. This algorithm formed the basis for several significant data storage system.

Image Compression using Open CL-Based Discrete Cosine Transform: Image Compression using Open Computing Language (OpenCL) [17] developed an efficient parallel implementation of the forward DCT and quantization algorithms for JPEG image compression. The efficient DCT and quantization algorithms were implemented for JPEG image compression using Open Computing Language (OpenCL). This Open-CL utilized a multi-core CPU and a General Purpose Computing to perform DCT and quantization computations.

The Open-CL also applied optimization technique to reduce the kernel execution time significantly. The method was evaluated in a heterogeneous environment, resulting in reducing the execution time and improving the data transfer operations (read, write). Hence, the algorithm applying open computing language was found to be more efficient leveraging the computing capabilities of modern computing systems.

Lossless Compression Method for Discrete Color Images: A Lossless Compression (LC) method [18] of discrete-color and binary images, such as map images, graphics, GIS, as well as binary images was developed aiming at improving the compression ratio. The method was designed based on two main components.

The first component in LC methods was a fixed-size codebook. The fixed-size codebook encompassed of an 8 × 8 bit blocks of two-tone data along with their corresponding Huffman codes and their relative probabilities of occurrence. The second component in LC method is the row-column reduction coding, which encode those blocks that were not in the codebook. The algorithm is given below (Figure 2).

The first phase in the design of codebook model consisted of trimming the margins in order to remove the redundant framework and biasing distribution of 8 × 8 blocks. Non-redundant frames were preserved to increase the relative probability of '8 * 8 *blocks*'. In the second phase, the image dimensions were modified in order to make them divisible by 8 for obtaining an integral number of 8×8 blocks. Next, the Row Column Reduction Coding removed redundancy between row vector and column vector of each block, therefore improving the compression ratio.

Color Space Transformations for Lossless Image Compression: Color Space Transformations (CST) [19] for Lossless Image Compression was based on the simple color space transformations RDgDb and LDgEb. One of the transformations, RDgDb, was designed on the basis of lossless ratios which required 2 integer subtractions per image pixel. On the other hand, LDgEb originated based on analog transformation from the human vision system. In CST algorithm, the distance between the primary colors of closer wavelengths 'R' – $G = Dg$ and $G – B = Db$ were investigated.

Width 'W', Height 'H'
//Code book model
Step 1: For each image with different sizes
Step 2: For each fixed part with '8 * 8' blocks
Step 3: For each variable part corresponding to the blocks
Step 4: Perform compression using salt-and-pepper
Step 5: Perform pre-processing
Step 6: Perform trimming to avoid biasing distribution
Step 7: Divide by 8 with the modified image
Step 8: End for
Step 9: End for
Step 10: End for
Step 11: If '$H \bmod 8 \neq$', then '$H = H + 8 - H \bmod 8$'
Step 12: If '$W \bmod 8 \neq$', then '$W = W + 8 - W \bmod 8$'
Step 13: Resultant new dimensions stored in '$\hat{H} * \hat{W}$'
Step 14: End if
Step 15: End if //row reduction
Step 16: For each '8 * 8' vector
Step 17: Generate Row Reference Vector denoted as 'r'
Step 18: Generate Column Reference Vector denoted as 'c'
Step 19: If '$r \parallel c$' are identical
Step 20: First vector eliminates the second vector (//reducing the block)
Step 21: End if
Step 22: If '$r \parallel c$' are not identical
Step 23: Both are preserved
Step 24: End if
Step 25: End for

Fig. 2: LC algorithm

Transformation is performed iteratively until best results were obtained. The other color space transformation LDgEb performs transformation, where '$L = \left(\frac{R+G}{2}\right) and\ Dg = R - G\ and\ Eb = B - L$'. This process is repeated until the end of the iteration process is reached or all the '$8 - bit$' RGT test images are investigated.

Proposed Method: In this paper, we extend the work of Color Space Transformations for Lossless Image Compression (CST) [19] to multispectral data through Discrete Wavelet Transform and address the issues of predetermined number of discrete colors in LC [18] through continuous tone images.

The pruning method called Coefficient-based Discrete Wavelet Transform (CDWT) for lossless image compression decomposes an image into coefficients called sub-bands based on neighboring pixel values that results in higher compression ratio without compromising the image quality. The two phases of the proposed Transformation and Coefficient-based Discrete Wavelet Transform for lossless image compression are (i) Coefficient-based Discrete Wavelet Transform and (ii) Probability-based Transformation for continuous images.

Coefficient-Based Discrete Wavelet Transform: The Coefficient-based Discrete Wavelet Transform splits or partitions the given input image into coefficients called sub-bands (i.e. each band possessing a spectral data, therefore corresponding to multi spectral data). The resulting coefficients obtained are then compared with a threshold value. The coefficient values lesser than the threshold value are set to zero and neglected for future reference. On the other hand, the value of coefficients greater than the threshold value forms the basis for encoding. The process of Coefficient-based Discrete Wavelet Transform is as given below.

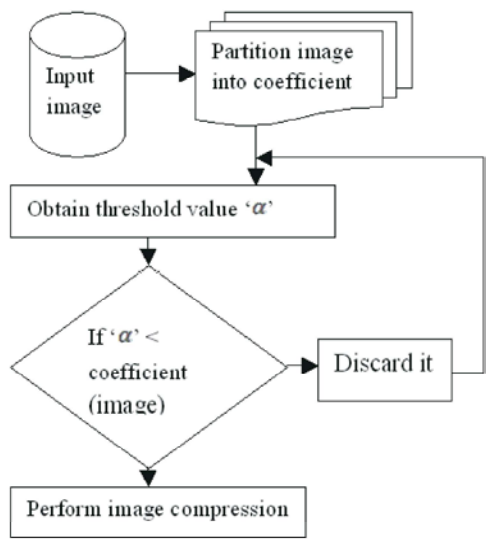

Fig. 3: Process of Coefficient-based Discrete Wavelet Transform

The process of transformation (as in Figure 3) for lossless image compression is applied to coefficients only from the high pass filter (i.e. neglecting the low coefficient values) with the objective of improving the compression ratio. Subsequently, the results obtained from the coefficients are given to the next level to obtain four sub-bands 'LL, LH, HL and HH'. This process is repeated up to the desired level of wavelet computation, resulting in the improved compression ratio. Figure 4 given below shows the algorithm.

Input: Input Image '$Image_i$ = $Image_1$, $Image_2$,...,$Image_n$', Threshold value 'α', Coefficient '$Coeff_i$ = $Coeff_1$,$Coeff_2$,...,$Coeff_n$'
Output: Improved compression ratio
Step 1: Begin
Step 2: For each Input Image '$Image_i$'
Step 3: Partition the input image into coefficients and store it in '$Coeff_i$'
Step 4: If '$Coeff_i < \alpha$' then
Step 5: '$Coeff_i$'
Step 6: End if
Step 7: If '$Coeff_i > \alpha$' then
Step 8: Perform lossless image compression with '$Coeff_i$'
Step 9: End if
Step 10: End

Fig. 4: Coefficient-based DWT algorithm

Probability-Based Transformation for Continuous Images: Transformation for lossless image compression for continuous images is an iterative process that includes column transformation and row transformation. The original input continuous image for lossless compression is of the form square. In column transformation, for each input images, initially the odd columns are obtained. Then the difference between the odd columns and its right neighbouring even columns are extracted. It is then stored in the buffer 'B'. Followed by this, the odd columns are stored in a different buffer 'I_{RF}' which is taken as input image to row transformation. The mathematical formulation for column transformation using lossless image compression with continuous image is as given below.

$$B(A+x, B+y) = I(x, 2y-1) - I(x, 2y) \quad (1)$$

$$NB'(x, y) = I_{RF}(x, 2y-1) \quad (2)$$

From (1) and (2) 'I' represents the Input image and 'B' represents the Original image, whereas the Modified input image is represented by 'NB' and the resultant value (i.e. odd columns) forms as the input image to row transformation '$I_{RF}(x, 2y-1)$'. The next step is row transformation where the difference between the odd rows and adjacent even rows are stored in first half rows of 'B'.

On the contrary, the odd rows are stored in a separate buffer 'NB' which is considered as input to next iteration. The resultant different value obtained is then stored in the tile format. Followed by this, encoding process using probability-based encoding is performed only if the value of the 'NB' is greater than the threshold value. Figure 5 given below shows the Probability-based encoding.

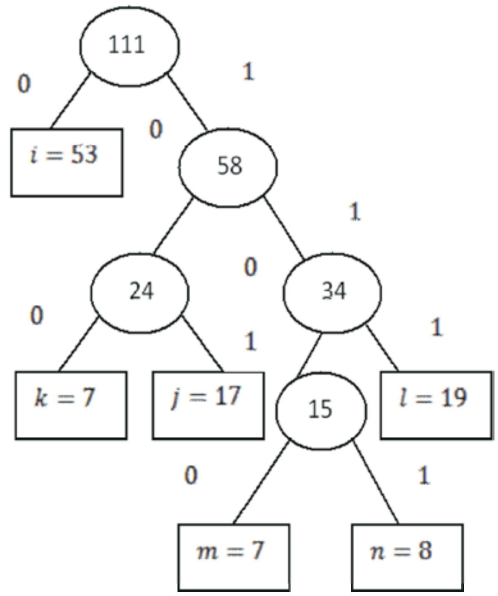

Fig. 5: Probability-based encoding

As shown in the figure, probability-based encoding is performed. As per probability-based encoding, the frequency of coefficients is arranged in ascending order. The image coefficient values (i.e. 'NB') that possess lowest frequency are selected to merge and the summation of two values is provided as input to the new coefficient (i.e. 'NB').

The same process is repeated for all image coefficient values until a single image coefficient value is reached at. Finally, the binary value of '0' or '1' is assigned, with lowest probability value assigned with '0' and highest probability value assigned with '1'. Figure 6 given below shows the algorithm.

As shown above, the Probability-based Transformation algorithm reduces the computational complexity involved during data transformation. Once, the Transformation is accomplished, finally, probability-based data un-transformation is carried out which is similar to that of data transformation. In probability-based data un-transformation, row un-transformation is performed followed by column un-transformation. This process is iterated at each image level.

Input: Input image '*I*', Original image '*B*', Modified input image '*NB*', Threshold value 'α'
Output: reduces computational complexity
//column transformation
Step 1: Begin
Step 2: For each Input image '*I*'
Step 3: Perform column transformation for lossless image compression using ()
Step 4: Obtain modified input image using ()
Step 5: End for
Step 6: For each 'NB_i'
Step 7: Sort the gray levels by decreasing probability
Step 8: Sum the two smallest probabilities
Step 9: Assign '1' to the highest probability and '0' to the lowest probability
Step 10: Sort the new value into the list
Step 11: Repeat step 7 to step 10 until only two probabilities arrives at
Step 12: End for
Step 13: End

Fig. 6: Probability-based Transformation algorithm

RESULTS

The improved lossless image compression model is tested under the simulation environment. The images for lossless image compression are obtained from "Waterloo Repertoire GreySet2" collection. These twelve images are all eight bits deep and range in size from 464_352 to 672_498 pixels. The evaluation of the proposed model is performed based on the factors, compression ratio, computational complexity and mean square error. The result of the experiments is presented below.

The table given below and the graph describe the performance result of the proposed model CDWT with the existing methods LT-TD [16], OpenCL [17], LC [18] and CST [19]. The compression ratio is measured based on the size of image present in the dataset. The value of the proposed CDWT model is compared with the existing LT-TD [16], OpenCL [17], LC [18] and CST [19] is illustrated in Table 1. Table 1 displays the compression ratios for seven different images with varying sizes in the range of 256KB – 512KB.

Compression ratio is used to measure the ratio of compression being made with respect to the uncompressed size (of image) to the compressed size (image). The actual image size is taken that represents the uncompressed size of the image and the compressed size using different methods are obtained. Finally, the ratio of uncompressed size to the compressed size gives the actual compression ratio.

Figure 7 shows the compression ratio during lossless image comparison based on the size of image in the dataset. As shown in the figure, by applying the CDWT model, compression ratio is improved even with the increase in the size of images in the dataset. In the case of the proposed lossless compression model, the CDWT perform better than the existing LT-TD [16], OpenCL [17], LC [18] and CST [19]. On average, the proposed CDWT outperforms the LT-TD by 5.55%, 9.81% compared to OpenCL, 12.07% compared to LC and 15.30% compared to CST respectively. In the proposed CDWT model, Coefficient-based Discrete Wavelet Transform is performed. With coefficient-based transform, the resulting coefficients obtained are compared with a threshold value and then lossless image compression is performed with different image of varying sizes. Furthermore, the transformation process is applied to coefficients only from the high pass filter and are subsequently provided and are repeated up to the desired level of wavelet computation that further improves the compression ratio for different set of images.

The computational complexity to perform lossless image compression with varying image sizes compared with the existing methods LT-TD, OpenCL, LC and CST is illustrated in Table 2.

The computational complexity is used to evaluate the time involved to perform the transformation for lossless image compression for continuous image. The actual image size is taken to measure the computational complexity. Next, the time involved for transformation using different methods is obtained. Finally, the product of image size and the time for transformation gives the computational complexity.

As shown in the Figure 8, the computational complexity is measured using 6 different images with three images (Bird, Bridge, Camera) with size 256KB and four images (Barb, Boat, Lean and Peppers) with size 512KB respectively. Compared to the existing methods, the proposed CDWT model involves lowest computational complexity for transformation with lossless image compression even when size of images increases. In the proposed CDWT model, probability-based transformation is performed for lossless image compression for continuous images that reduces the computational complexity. Moreover, rows and columns are stored separately in the buffer that involves row and

Table 1: Compression ratio comparison

	Compression ratio (%)				
Image (KB)	CDWT	LT-TD	OpenCL	LC	CST
Bird	88.23	83.15	79.25	77.13	74.18
Bridge	90.14	85.06	81.16	79.11	76.16
Camera	89.35	84.27	80.37	78.32	75.37
Barb	91.82	86.75	82.85	80.80	77.86
Boat	92.22	87.14	83.24	81.19	78.24
Lena	93.48	88.40	84.50	82.45	79.49
Peppers	95.19	90.11	86.21	84.16	81.19

Table 2: Computational complexity

	Computational complexity (s)				
Image (KB)	CDWT	LT-TD	OpenCL	LC	CST
Bird	1.55	1.94	2.01	2.08	2.14
Bridge	1.59	1.99	2.09	2.12	2.19
Camera	1.65	2.05	2.15	2.18	2.25
Barb	1.84	2.24	2.32	2.43	2.65
Boat	1.89	2.29	2.35	2.51	2.69
Lena	1.95	2.35	2.41	2.56	2.74
Peppers	1.98	2.38	2.49	2.60	2.78

Table 3: Mean Square Error Comparison

	Mean Square Error (dB)				
Image	CDWT	LT-TD	Open CL	LC	CST
Bird	8	10	11	12	14
Bridge	11	13	15	17	19
Camera	14	17	19	21	24
Barb	18	22	24	25	28
Boat	15	20	23	24	28
Lena	21	25	28	32	35
Peppers	24	31	32	34	38

column transformation. Only odd columns and row are used where the resultant value is stored in tile format and compared with the threshold. The encoding process is finally performed only if the new resultant value is greater than the threshold that helps in minimizing the computational complexity during transformation for lossless image compression by 22.59% compared to LT-TD, 27.31% compared to OpenCL, 32.44% compared to LC and 39.91% compared to CST respectively.

Table 3 provides an insight into the mean square error using the proposed CDWT and the existing methods, LT-TD, OpenCL, LC and CST respectively.

Mean square error is used to estimate the difference between the original image (size) and the decompressed image (size). Lower the mean square error, more efficient the method is said to be and is measured in terms of decibels (dB).

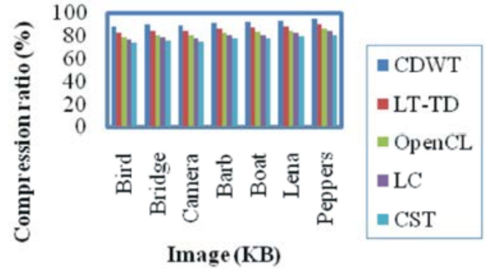

Fig. 7: Image Compression ratio

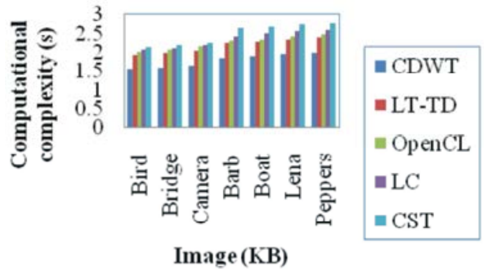

Fig. 8: Computational complexity

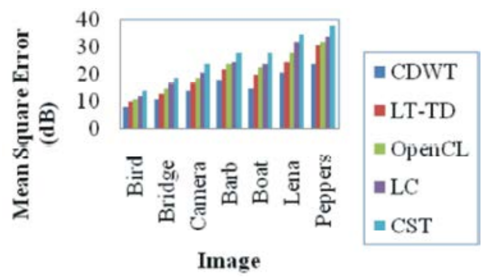

Fig. 9: Mean Square Error on Image Compression

Figure 9 illustrates the mean square error with respect to seven different images obtained from "Waterloo Repertoire GreySet2". By applying Coefficient-based DWT algorithm, lossless image compression is applied to coefficients only from the high pass filter, error ratio is reduced by 24.05% to LT-TD and 37.55% compared to OpenCL. Moreover by applying probability-based encoding, the frequency of coefficients is arranged in ascending order that further minimizes the mean square error by 49.64% and 69.48% compared to LC and CST respectively.

CONCLUSION

Image compression is one of the key issues in the image processing. Transformation is developed for lossless image compression and image components are obtained by transformation of color space. This paper presents an emergence of new lossless image compression model called CDWT (Transformation and Coefficient-based Discrete Wavelet Transform). To overcome the limitations of existing image compression model three parameters such as the compression ratio, computational complexity and mean square error is taken into account along with Coefficient-based DWT algorithm for performing lossless image compression based on the threshold value from which it is identified that the proposed Coefficient-based DWT algorithm has the improved compression ratio. Besides, a probability-based Transformation method for continuous images to reduce the computational complexity and mean square error during transformation is introduced. Performance results revealed that the proposed CDWT model provides 13.69% compression ratio by reducing the computational complexity compared to the state-of-the-art methods.

REFERENCES

1. Garima Chopra and A.K. Pal, 2011. "An Improved Image Compression Algorithm Using Binary Space Partition Scheme and Geometric Wavelets", IEEE Transactions on Image Processing, 20(1): 270-275.
2. Anandan, P. and R.S. Sabeenian, 2014. "Curvelet based Image Compression using Support Vector Machine and Core Vector Machine – A Review", International Journal of Advanced Computer Research, 4(15): 1-7.
3. Han Oh, Ali Bilgin and Michael W. Marcellin, 2013. "Visually Lossless Encoding for JPEG2000", IEEE Transactions on Image Processing, 22(1): 189-201.
4. Aur´elien Bourquard and Michael Unser, 2013. "Binary Compressed Imaging", IEEE Transactions on Image Processing, 22(3): 1042-1055.
5. Kamil Dimililer, 2013. "Backpropagation Neural Network Implementation for Medical Image Compression", Hindawi Publishing Corporation, Journal of Applied Mathematics, pp: 1-9.
6. Nur, Azman Abu and Ferda Ernawan, 2014. "A Novel Psychovisual Threshold on Large DCT for Image Compression", Hindawi Publishing Corporation, The Scientific World Journal, pp: 1-12.
7. Hanaa ZainEldin , Mostafa A. Elhosseini, Hesham A. Ali, 2015. "Image compression algorithms in wireless multimedia sensor networks: A survey", Elsevier, Ain Shams Engineering Journal, 6(2): 481-490.
8. Fernando Alves, Vinicius Cogo, Sebastian Wandelt, Ulf Leser and Alysson Bessani, 2015. "On-Demand Indexing for Referential Compression of DNA Sequences", Plos One, 10(7): 1-17.
9. Haider Al-Mahmood, Zainab Al-Rubaye, 2014. "Lossless Image Compression based on Predictive Coding and Bit Plane Slicing", International Journal of Computer Applications, 93(1): 1-6.
10. Devang kumar Shah and Chandresh Vithlani, 2014. "VLSI-Oriented Lossy Image Compression Approach using DA-Based 2D-Discrete Wavelet", The International Arab Journal of Information Technology, 11(1): 59-68.
11. Jagadish H. Pujar, Lohit M. Kadlaskar, "A New Lossless Method of Image Compression and Decompression Using Huffman Coding Techniques", Journal of Theoretical and Applied Information Technology, 15(1): 1-6.
12. Manpreet Kaur, Vikas Wasson, 2015. "ROI Based Medical Image Compression for Telemedicine Application", Elsevier, Procedia Computer Science, 70: 579-585.
13. Rajeswari, C. and S. Prakasam, 2014. "Using Discrete Cosine Transform 2 to achieve High Peak Signal-to-Noise Ratio in Image Processing", International Journal of Computer Applications, 98(10): 1-5.
14. Nadeem Akhtar, Gufran Siddiqui and Salman Khan, 2014. "A Novel Image Compression Technique using Simple Arithmetic Addition", Proc. of Int. Conf. on Recent Trends in Information, Telecommunication and Computing, pp: 1-9.
15. Ian Blanes, Enrico Magli, Joan Serra-Sagrist, 2014. "A Tutorial on Image Compression for Optical Space Imaging Systems", IEEE Geoscience and remote sensing magazine (IEEE), 2(3): 8-26.
16. Lei Wang, Jing Bai, Jiaji Wu and Gwanggil Jeon, 2015. "Hyperspectral image compression based on lapped transform and Tucker decomposition", Elsevier, Signal Processing: Image Communication, 36: 63-69.
17. Nasser Alqudami and Shin-Dug Kim, 2015. "OpenCL-based optimization methods for utilizing forward DCT and quantization of image compression on a heterogeneous platform", Springer, Journal of Real-Time Image Processing, pp: 1-17.

18. Saif, Alzahir and Arber Borici, 2015. "An Innovative Lossless Compression Method for Discrete-Color Images", IEEE Transactions on Image Processing, 24(1): 44-56.
19. Roman Starosolski, 2014. "New simple and efficient color space transformations for lossless image compression", Elsevier, Journal of Visual Communication and Image Representation, 25(5): 1056-1063.